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ON THE USE OF HIERARCHICALLY COMPUTED 'MEXICAN HAT' FEATURES FO--ETC(U)

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6 ON THE USE OF HIERARCHICALLY COMPUTED "MEXICAN HAT" FEATURES FOR TEXTURE DISCRIMINATION.

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ABSTRACT

Bandpass Laplacian-like operators derived by a hierarchical discrete correlation technique provide natural measures of texture coarseness. The performance of these measures on a standard set of geological terrain types is comparable to that of conventional texture features that do not use directional information.

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1. Introduction

In texture segmentation it is appropriate to process the image with operators of many sizes. This is computationally expensive because many computational steps are required for each location in the image.

In [1], Burt describes an elegant hierarchical discrete correlation (HDC) method for computing the correlation between an image and a kernel. In this approach correlations at upper levels can be computed as the weighted sums of correlations with narrower kernels at lower levels. Kernels which can be computed hierarchically in this way closely approximate the Gaussian probability distribution. This means that correlation is equivalent to low-pass filtering.

The principal advantage of the HDC method is that it is computationally more efficient than the direct correlation and FFT methods. In addition, correlations for a set of scaled kernels are computed at once, without any need to construct and store large kernels or kernels of different shapes and sizes. Samples of the correlations obtained at nearby image positions can be summed to obtain e.g. band-pass Laplacian ("Mexican hat") operators. Mexican hat filtered images are essentially the same as the differences of Gaussian filtered channels observed in the human visual system [2].

Band-pass filtering responds to details of the image which contain a limited range of spatial frequencies. This reflects the coarseness of the texture. Thus, features derived from band-pass filtered images on different frequency bands might be useful for texture classification. The local computation of these textural properties could be an aid to image segmentation using cooperative hierarchical computation [3].

In this note we apply Mexican hat filtering to 180 LANDSAT imagery samples belonging to three geological terrain types. The averages of the squared outputs computed over band-pass filtered images are used as texture features in a Fisher linear discriminant classification. The results are compared to the results obtained by Weszka et al. [4].

Nondirectional Mexican hat features did not yield as good classification results as some of the statistical texture features using directional information. Their performance was more comparable to that of features derived from the Fourier power spectrum. In any case, Mexican hat features seem to give a good measure of texture coarseness. Combined with other measures, they should be useful for texture segmentation.

2. Approach

2.1 Mexican hat filtering

The band-limited Laplacian ("Mexican hat") may be formally defined as the Laplacian of a Gaussian $\Delta^2 G$, but the result is generally approximated as the difference between two Gaussian functions which have different standard deviations [1] [2],

$$L(x,y) = \frac{1}{2\pi} \frac{e^{\frac{-(x^2+y^2)}{2\sigma_1^2}}}{\sigma_1^2} - \frac{1}{2\pi} \frac{e^{\frac{-(x^2+y^2)}{2\sigma_2^2}}}{\sigma_2^2}$$

Typically, the ratio σ_2/σ_1 is in the range of 1.5 to 2.5.

Burt defined three types of HDC. In type 1 an odd number and in type 2 an even number of correlations with small kernels are summed to obtain the correlation with the next larger kernel, while type 3 is for fractional values. He also defined a reduced form of HDC in which the number of samples is reduced by a factor of r^2 from level to level.

Let $g_\ell(x,y)$ be the correlation function at hierarchical level ℓ. It was obtained from the original image $f(x,y)$ through ℓ recursions of a correlation-like operation using the weighting function $w(x,y)$. The sample distance grows geometrically by the factor r from level to level; thus r is said to be the order of the HDC.

A band-limited Laplacian with a ratio $\sigma_2/\sigma_1 = r$ may be obtained from the type 1 HDC of order r by subtracting $g_{\ell+1}(x,y)$ from $g_\ell(x,y)$. If the reduced form of the HDC is used, samples of $g_{\ell+1}(x,y)$ are not computed for every sample of $g_\ell(x,y)$. Missing samples are obtained by applying $w(x,y)$ to the neighborhood of $g_\ell(x,y)$.

To obtain ratios $\sigma_2/\sigma_1 < r$ two HDC's (of any type) are computed with different generating kernels. The Laplacian operator is then a difference between corresponding samples in the two HDC's.

For $\sigma_2/\sigma_1 > r$, first an HDC of any type is obtained to form the central Gaussian. Then the surround Gaussian is obtained by applying the generating kernel in reverse. For type 1 we have

$$L_{n_x,n_y,\ell} = g_{n_x,n_y,\ell} - r^2 \sum_{i=-m}^{m} \sum_{j=-m}^{m} w(i,j)\, g_{\frac{n_x-i}{r},\, \frac{n_y-j}{r},\, \ell+1}$$

The sums in this expression are understood to include only those terms for which $\frac{n_x-i}{r}$ and $\frac{n_y-j}{r}$ are integer valued. The equal contribution constraint on w ensures that the sum will have a total weight of $1/r^2$, hence the r^2 factor normalizes the sum in the above definition.

A one-dimensional example using this procedure is shown in Figure 1 [1]. Here a ratio $\sigma_2/\sigma_1 = 2.5$ is obtained with a type 1 HDC, order r=2, kernel width k=5, and with a separable generating kernel with weight vector w = (.05,.25,.4,.25,.05). The Mexican hat filtering algorithm used in our study was based on this third procedure.

2.2 Features and classifier

As a result of the hierarchical computation, we have an order N pyramid, in which the lowest level represents the highest spatial frequency band. Its dimensions are the same as in the original image. Image array dimensions are decreased by half from level to level, and these levels represent lower frequency bands.

Let $L_{i,j,\ell}$ be the value of the filtered image at point (i,j) on level ℓ. Texture feature LAP is defined as an average of the squared values computed over the filtered image:

$$LAP(\ell) = \frac{1}{2\exp(N+1-\ell)\ 2\exp(N+1-\ell)} \sum_{i=1}^{2\exp(N+1-\ell)} \sum_{j=1}^{2\exp(N+1-\ell)} L^2_{i,j,\ell}$$

for $\ell=1,2,\ldots,N$. For a 64 by 64 image, for example, we have six features. The first of these is computed over a 64 by 64 image and the last one over a 2 by 2 image.

The classifier used in this study was the same Fisher linear discriminant classifier as in [4].

2.3 Image data

The same imagery as in the main study of [4] was used. It comprises a set of 180 LANDSAT terrain samples, belonging to three geological terrain types: Mississippian limestone and shale; Lower Pennsylvanian shale, and Pennsylvanian sandstone and shale (labeled A, B and C). The gray scale has been modified to cover just 64 gray levels and histogram flattening has been performed on each of these 180 terrain samples to remove effects of unequal brightness and contrast.

3. Experiments

First a pilot study was performed by using different generating kernels in filtering. The generating kernels used were:

w1 = (.05,.25,.4,.25,.05), w2 = (.13,.37,.37,.13) and w3 = (.2,.6,.2). Here w1 and w2 are the most Gaussian-like kernels for kernel widths 5 and 4. The w3 kernel is not Gaussian-like, but it was used in this study because it accentuates high spatial frequencies. Using these kernels first ten terrain samples of each type were processed. The results were quite similar for each of these kernels. It seemed that none of these was able to discriminate very well terrain types A and B, while each of them was able to discriminate type C. Kernel w2 was selected for the main study because it has smaller border effects than w1 at upper pyramid levels.

In the main study all of the 180 terrain samples were processed using kernel w2. As a result we got six feature values for each terrain sample, each of them corresponding to a different spatial frequency band. The distributions for some of these features are presented in Figure 2.

The Fisher linear discriminant classification method was used to classify the terrain samples into three classes by using single features and pairs of features. The sixth feature was not used in classification because its values seemed to be randomly distributed, having no correlation with the different terrain types. Classification results for single features are presented in Table 1a and for pairs of features in Table 1b.

4. Discussion and conclusions

A direct comparison to results of Weszka et al. [4] is difficult because our features have no directional component. In [4], the features were computed for all pixel sizes (frequency bands) in four directions, and all features and feature pair combinations were used in classification. Neither are the frequency bands used in these studies exactly equal. However, by computing the averages of the classification results of the earlier study for each frequency band, we can have a rough estimate of the performance of the LAP features. In Tables 2a and 2b are presented the averages of the classification results in [4] for the Fourier and "CONTRAST" (computed on single points or on averages) features. The best classifications for each size are presented in brackets.

The following can be seen from these results:

1. Features based on Mexican hat (LAP) filtering do not quite as well as features based on second-order statistics, and do about equally well as Fourier features. The absence of directional information reduces the performance of the LAP features. However, their performance does not degrade as rapidly with increasing size as does that of the Fourier and statistical features.
2. Results for terrain type C are very good. Using a single feature only one of the type C samples was misclassified. This result is better than the results of most of the experiments using feature pairs in [4].

3. Discrimination of terrain types A and B is quite poor. The distributions of features at level 2 (Figure 2) show that the feature values of the misclassified samples are quite different from the values of the other samples belonging to the same terrain type.

These results indicate that the LAP features give a good measure of texture coarseness, but in order to get better classification accuracy some additional measures are needed. Probably these samples are more appropriately modeled statistically in the space domain, rather than as sums of sinusoids, and statistical features captured the essential differences more effectively [4]. This is also in agreement with the results of Conners and Harlow [5].

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Feature number	Correctly classified	Misclassified A's	Misclassified B's	Misclassified C's
1	121	33	25	1
2	85	16	48	31
3	122	30	23	5
4	105	38	16	21
5	80	48	19	33

Table 1a. Results using single features

Feature pair	Correctly classified	Misclassified A's	Misclassified B's	Misclassified C's
1,2	147	15	16	2
1,3	126	27	26	1
1,4	137	21	20	2
1,5	132	24	22	2
2,3	140	17	17	6
2,4	131	20	21	8
2,5	110	18	30	22
3,4	131	25	19	5
3,5	126	28	21	5
4,5	107	38	15	20

Table 1b. Results using pairs of features

Feature pair	Fourier	CONTRAST COOC (points)	CONTRAST COOC (average gray levels)	LAP
Size 1, Size 1	142.8(158)	151.5(166)	151.5(166)	-
Size 1, Size 2	139.3(151)	146.3(166)	143.5(158)	147
Size 1, Size 3	133.1(144)	138.6(153)	139.1(155)	126
Size 1, Size 4	128.4(137)	130.7(140)	138.6(152)	137
Size 2, Size 2	116.5(135)	141.0(154)	118.8(142)	-
Size 2, Size 3	117.4(134)	132.1(148)	130.6(151)	140
Size 2, Size 4	107.1(126)	126.3(140)	129.5(146)	131
Size 3, Size 3	117.2(122)	119.5(133)	129.8(144)	-
Size 3, Size 4	109.7(120)	109.6(126)	128.8(139)	131
Size 4, Size 4	98.7(109)	93.7(110)	121.5(130)	-

Table 2a. Average values of classification results for pairs of features.

Feature	Fourier	CONTRAST (points)	CONTRAST (averages)	LAP
Size 1	124.0(133)	129.5(136)	129.5(136)	121
Size 2	95.8(108)	120.3(126)	97.0(112)	85
Size 3	100.0(111)	100.8(113)	112.8(117)	122
Size 4	87.0(95)	82.3(99)	111.8(117)	105

Table 2b. Average values of classification results for single features.

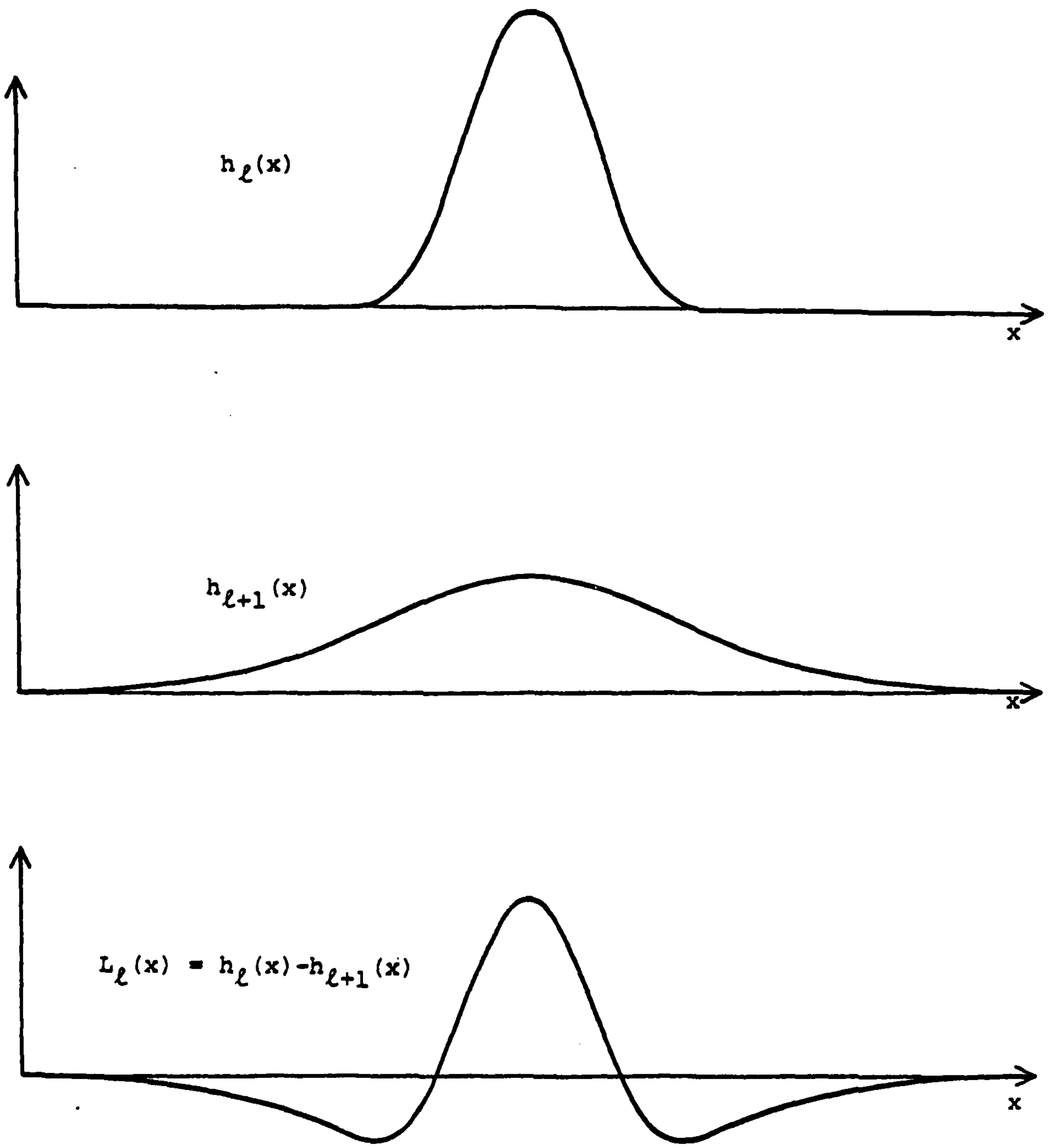

Figure 1. One-dimensional "Mexican hat" operator

LAP(1)

Value	No. of times obtained A	B	C
75			3
80			3
85			3
90			6
95			10
100			9
105			10
110		1	7
115			2
120		3	6
125	2	4	1
130	3	3	
135	5	4	
140	10	2	
145	6	7	
150	8	7	
155	13	6	
160	7	11	
165	4	6	
170	1	4	
175	1	1	
180		1	

LAP(2)

Value	No. of times obtained A	B	C
54			1
56	2		
58	1	1	
60	6	4	
62	10	2	2
64	11	2	1
66	14	7	4
68	1	4	5
70	10	8	2
72	4	2	10
74		5	10
76	1	3	4
78		7	7
80		7	7
82		3	4
84		1	1
86		1	1
88			
90		2	1
92		1	

LAP(3)

Value	No. of times obtained A	B	C
20		1	
22	3	6	
24	2	7	
26	10	15	
28	12	8	1
30	15	10	
32	9	5	2
34	4	2	2
36	3	2	2
38	1	2	2
40		2	5
42	1		7
44			6
46			3
48			6
50			6
52			6
54			3
56			3
58			3
60			3

Figure 2. Distributions of feature values

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